OPTICAL TRACKING OF BARBELL KINEMATICS FOR LOW-COST STRENGTH TRAINING PERFORMANCE MONITORING: A PILOT STUDY

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Velocity based training (VBT) is a promising method to quantify and direct resistance training. Recent advances in computer science have opened the way for low-cost methods to measure VBT using video data from a smartphone. This work introduces and analyses the feasibility of a computer vision-based Python application in tracking barbell kinematics during VBT, compared against Vicon data during the back squat in one subject. As input into the algorithm, sagittal-plane video data is needed with the barbell plate in focus. Time of the concentric part of the squat and vertical barbell displacement are then automatically tracked using OpenCV libraries. The time parameter was accurately assessed using two different OpenCv Tracker, the KCF (r=0.83, SEE=0.02s) and the MOSSE (r=0.81, SEE=0.02s) tracker, respectively. For the vertical displacement, a lower accuracy was obtained using KCF (r=0.36, SEE=0.02m) and MOSSE (r=0.62, SEE=0.01m). Tracking errors could be explained by the camera set-up, as well as differences in frame rates between the video and the Vicon data. It might be possible to correct these errors in future work using machine learning techniques. This pilot study shows the feasibility of a computer vision-based Python application to measure barbell kinematics in a low-cost manner and might play a part towards advancing VBT monitoring technologies for widespread use.

KEYWORDS: velocity-based training, resistance training monitoring, barbell kinematics, computer vision, python, sports technology

INTRODUCTION

Resistance training (RT) is widely known to improve athlete performance by increasing muscle mass, maximal strength and power output. However, one key challenge with RT is to objectively monitor training intensity and actual training load for maximizing training benefits (González-Badillo & Sánchez-Medina, 2010). Different approaches exist to monitor training intensity using either objective or subjective methods. A promising objective method to quantify and direct RT intensity is velocity based training (VBT) (Suchomel et al., 2021). VBT covers a wide range of applications in strength training. It can be used to improve percentage-based training in form of feedback to improve motivation and competitiveness as well as a tool to prescribe and apply training programs. By monitoring changes in the speed of exercise execution, the fatigue of an athlete can be measured. Furthermore, there exists a demonstrated linear relationship between lifting velocity and intensity as percentage of maximum ability, allowing the determination of the one repetition maximum without risk of injury due to heavy lifting (Weakley et al., 2021).
In recent years, mobile activity tracking devices have emerged for RT monitoring, representing the number one fitness trend today (Thompson, 2021). In particular, smartwatch and smartphone applications have emerged as reasonable and more convenient alternatives to assess kinematic parameters (e.g. position, displacement, velocity, accelerations) during VBT compared to so-called linear position transducers (Balsalobre-Fernández et al., 2018; Oberhofer et al., 2021). These advances in mobile technologies are opening the way for research and sports facilities with less funding to monitor VBT intensity, and thereby, playing a part towards creating equal opportunities in sports.
Building on these most recent trends, the motivation for the present study was to develop a computer vision application that allows convenient and low-cost tracking of barbell kinematics for monitoring of VBT based on video data, and scientifically validate the application against data from marker-based optical motion capture as gold standard. The application is written in the Python programming language, operating system independent, free of any costs and well documented. To facilitate further shared development and contribution, the programming code

is planned to be provided via a public GitHub repository to the community. Thus, an extension of the present application, and alteration according to individual needs, are feasible.

METHODS

A motion capture algorithm for video-based analysis of barbell kinematics was developed using the high-level programming language Python and OpenCV libraries. As input into the algorithm, sagittal-plane video data is needed with the barbell plate in focus, as well as user-defined barbell plate diameter and plate color. Barbell displacement is then automatically tracked as follows: 1) Selection of region of interest (ROI), 2) computation of centre of ROI, 3) derivation of the centre of the barbell for each frame via OpenCV tracker and 4) smoothing of trajectory using a simple moving average filter (windows size 17). From the tracked barbell centre, the displacement and the time per concentric phase for each repetition are calculated by automatically segmenting the turning point and start/end points of each set. Two different open source trackers were considered for implementation into the Python application and compared in the present study, namely the KCF (Kernelized Correlation Filter) and the MOSSE (Minimum Output Sum of Squared Error (*OpenCV Cv::Tracker Class Reference*).

One healthy subject (male, 28 years old) volunteered to perform back squats for validating the Python algorithm against data from marker-based optical motion capture. The participant had experience with free-weight training. Ethical approval for this study was given by the Kantonale Ethikkommission (KEK). Ten sets of 10 repetitions of back squats were performed (40kg lifting weight), separated by one to three minutes rest between the sets. Real-world conditions were applied as the participant was able to choose concentric and eccentric speed autonomously. However, a clear pause in the full standing position was taken between each repetition.

For the data collection, one video recording device (Galaxy S7 Samsung, Seoul South Korea) was placed perpendicular to the weight plates. The video data was transferred to a computer (MacBook Air, Apple Inc., Cupertino, CA, USA) for further analysis. The recording device was placed in a way as it would most probably be placed in a gym setup (perpendicular, slightly upwards facing). Sampling rate for the video recording device was 30 Hz. Simultaneously, six infrared cameras (Vantage 5, Vicon Motion Systems Ltd., Oxford, UK) were placed around the participant to record the motion of the barbell. Six reflective markers were fixated on the left end, and seven markers (for better detection of the barbell orientation) on the right end, respectively. The Vicon cameras were controlled from an Antec WorkBoy desktop (Antec, Taipei, Taiwan) running Vicon Nexus software (version 2.9, Vicon Motion Systems Ltd., Oxford, UK). Sampling rate for the motion capture data was 100 Hz.

For validation purposes, the position and displacement of the midpoint of the barbell was determined based on the Vicon data and compared against the results from the Python application. All data was filtered with a simple moving average filter (window size 5), and then, the displacement and time of concentric phase was determined for each repetition. Concentric phases were automatically segmented at the beginning and end of areas with a vertical velocity threshold of 0.05 m/s. The segmentation of each set was visually assessed for quality control.

For statistical analysis of the results, according to (Hopkins, 2000), the validity of the measurements was assessed by calculating the Pearson’s correlation coefficient (r), a calibration equation and the standard error of estimate (SEE). In particular, the accuracy was assessed using the calibration equation and SEE; while precision was assessed using the Pearson’s correlation coefficient. In addition, the Intraclass correlation coefficient (ICC 2.1) was chosen according to (Koo & Li, 2016) to test the level of agreement between both measurement methods. Values between 0.5 to 0.75 were considered as moderate, from 0.8 to 0.9 as good, and above > 0.9 as excellent (Koo & Li, 2016). For the calibration equation an ordinary least product (OLP) regression was used based on (Ludbrook, 1997). SEE was calculated as

$$SEE = \sqrt{\frac{1}{n-2} * \sum_{i=1}^{n} [Y_i - (a + bX_i)]^2} \quad (1)$$

whereby Xi and Yi are the individual device and criterion data points, respectively, while a and b are the intercept and slope from the OLP regression (Siegel, 2016).

RESULTS

A total of 100 repetitions of back squats were recorded and compared. In Table 1 the results of the statistical analysis are listed.

Accuracy: For the time parameter, the calibration equation shows a higher accuracy than for the vertical displacement parameter. Both parameters show signs of proportional and fixed bias observed in the mean and in the calibration equation with a SEE of 2.15% for the time parameters and 1.94-2.88% for the vertical displacement, respectively. Precision: The Pearson's r coefficient shows the better correlation for the time parameter, while the vertical displacement is weakly correlated. In particular, the KCF tracker shows a weak correlation. These results are supported by the ICC values, with ICC=0.600 for MOSSE and ICC=0.326 for KCF, respectively (Table 1).

Table 1: Comparison of the predicted time and displacement parameters between Vicon and the Python application, using the KCF and the MOSSE tracker, respectively. The mean Δ parameter describes the actual mean difference between the Vicon data and the Python data for all the recorded repetitions of the back squat (i.e. 100 repetitions).

Tracker	Parameter	Mean Δ (std)	Slope	Intercept	Pearson's r	ICC	SEE (%)
KCF	time [s]	0.02(0.016)	1.153	-0.141	0.829	0.806	0.017(2.15%)
MOSSE	time [s]	0.018(0.016)	1.124	-0.116	0.812	0.799	0.017(2.15%)
KCF	displacement [m]	0.025(0.016)	1.559	-0.384	0.361	0.326	0.019(2.88%)
MOSSE	displacement [m]	0.018(0.011)	1.378	-0.261	0.619	0.600	0.012(1.94%)

DISCUSSION

The time of the concentric phase of the squat was slightly underestimated using the Python application compared to Vicon as gold standard. Low discrepancies between the Python application and the Vicon data were expected as the time parameter does not depend on the magnitude of barbell displacement. However, the sampling rate of the videos is 30 frames per second (fps) which leads to a resolution of around 0.03s and is of the factor 3 larger than the fixed bias. This could explain the difference in the time parameter between the Python application with video data of 30 fps and Vicon with 100. The underestimation error in the prediction of vertical displacement using the Python application is likely originating from the positioning of the camera with respect to the barbell. A well-known error is introduced in the reconstruction of vertical barbell displacement if the camera is not aligned perpendicular to the sagittal plane of exercise execution. However, ensuring ideal alignment of the camera with respect to the sagittal plane of motion is difficult in the real-world training-specific scenario. Moreover, the optimal alignment is likely dependent on exercise type and distance from the recording device to the athlete. Part of the error could also be due to discrepancies between the motion of the barbell's midpoint (Vicon) and its outer extremity (video). Fritschi et al. 2021 found the order of these errors to be around 3–5% which implies the need for a more detailed investigation.

Thus, one might ask how accurate mobile activity trackers must be in a real-world setting, and which parameters are needed, for best assisting athletes during VBT. While further investigation is needed into how good a 4% error in vertical barbell displacement is, particularly if speed is to be derived as the first derivative, the resulting time parameter with an accuracy of around 1.2% can already provide valuable feedback to athletes in terms of changes in execution speed during different sets and repetition cycles to monitor progress in VBT. Furthermore, novel approaches in machine learning and artificial intelligence are emerging, which may help to apply a correction factor for offsetting displacement errors in future work.

CONCLUSION

Despite some remaining challenges, this work shows promising results of a video-based Python application to monitor barbell kinematics during the back squat in one subject. While the displacement outcome parameters must currently be interpreted with caution, the accuracy in the time parameter is promising. Further validation of the proposed application in more subjects and different strength exercises is planned. Also, the derivation of velocity parameters based on barbell displacement will help to gain further insights into the validity and usefulness of the proposed application. As VBT represents a rather new method to measure training load, its full potential might still be undiscovered. However, as the market around VBT devices grows, it has to be ensured that any new device or method is scientifically validated before using it in the training-specific environment, as the results are not trustworthy otherwise. Here, the results of the present study might play a part towards advancing state-of-the-art technology for science-based, low-cost VBT monitoring.

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